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The Use of Data Envelopment Analysis for Product Recovery

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ABSTRACT

The latest enhancements in industrial technologies, especially the ones in electronics industry, have provided organizations with the ability to manufacture faster and more economical products. This fact, coupled with the growing interest and demand for the latest technology, have led electronic equipment manufacturers to start producing "high-tech" and "personalized" products at an increasing rate. This has led to a high rate of obsolescence for electronic products worldwide, even though the majority of these "obsolete" products still function. In this paper, we investigate a product recovery facility where the end-of-life (EOL) products are taken back from the last users and are brought into the facility for processing. We assume that there are multiple types of EOL products and that a combination of these can be disassembled to provide for a sufficient number of demanded components and materials. We then present a data envelopment analysis (DEA) algorithm to determine the number and types of the EOL products that will be required to fulfill the demand. A numerical example is presented to demonstrate the functionality of the methodology.

Keywords: End-of-Life Processing, Product Recovery, Data Envelopment Analysis.

1. INTRODUCTION

The latest enhancements in industrial technologies, especially those in the electronics industry, have provided organizations with the ability to manufacture faster and more economical products. This fact, coupled with the growing interest and demand for the latest technology, have led electronic equipment manufacturers to start producing "high-tech" and "personalized" products at an increasing rate. This has led to a high rate of obsolescence for electronic products worldwide, even though the majority of these "obsolete" products still function. One of the most efficient ways to compensate for the financial and environmental burden of this obsolescence is to process and recover products at the end of their lives.

In the majority of end-of-life (EOL) processing operations, a certain level of disassembly is necessary. Even for disposal, the hazardous contents must be separated from the product and carefully processed before the residual product is disposed of. *Disassembly* is the process of systematic removal of components and/or materials from the original assembly so that there is no impairment to any useful constituent. Disassembly can be *partial* (where the product is not fully disassembled) or *complete* (where the product is fully disassembled) and may use a methodology that is *destructive* (focusing on materials rather than component recovery) or *non-destructive* (focusing on component rather than material recovery). In this paper, we consider the case of complete disassembly where the components are extracted from the product structure by either destructive or non-destructive methodology.

We investigate a product recovery facility where the (EOL) products are taken back from the last users and are brought into the facility for processing. We assume that there are multiple types of EOL products and that a combination of these can be disassembled to provide for a sufficient number of demanded components and materials. When multiple products consisting of a large number of components are considered, the problem of selecting an efficient combination of these

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products becomes combinatorial in nature. As the number of EOL products increase, the problem complexity increases exponentially. Therefore, using exhaustive search methods to obtain the efficient combination of the EOL products is impractical due to time and costs constraints. Hence, using a filtering technique to gain insight into the efficiency of each EOL product as well as to decrease the number of EOL products involved (by eliminating the relatively inefficient ones) provides for a significant time reduction. In this paper, we present a data envelopment analysis algorithm for product selection in the presence of multiple goals and constraints.

2. LITERATURE REVIEW

In recent years, data envelopment analysis (DEA) has gained popularity as a decision-making tool. DEA is especially efficient as a filtering technique when there is a crucial need to reduce the number of alternatives in a decision making process. For this reason, it has been applied by many researchers as a filtering technique rather than a selection methodology[2,7].

Sarkis and his collegeaues have written a series of papers involving the use of DEA. Sarkis and Cordeiro[16] investigated the relationship between environmental and financial performance at the firm's level. In a subsequent paper, Sarkis[13] proposed a two-stage methodology to integrate managerial preferences and environmentally conscious manufacturing (ECM) program. Talluri et al.[20] used DEA and Goal Programming methods for a Value Chain Network (VCN) considering the cross efficiency evaluations of Decision Making Units (DMUs). Sarkis[14] provided a comparative study investigating the efficiency of the DEA technique compared to the conventional multiple criteria decision making (MCDM) tools and concluded that DEA seemed to perform well as a discrete alternative MCDM tool. Sarkis and Weinrach[17] used DEA to evaluate environmentally conscious waste treatment technologies. Sarkis[15] explained how DEA can be used to improve ecoefficiency.

Various researchers have studied disassembly, it being one of the primary elements for product recovery. Gupta and Taleb[5], Taleb and Gupta[18], and Taleb et al.[19] studied disassembly scheduling. Kuo[9] analyzed the cost of disassembly in electromechanical products. Veerakamolmal and Gupta[21,22] conducted studies in the context of multi-period disassembly environment. Moore et al.[11] used Petri-nets to disassemble products with complex AND/OR relationships. Kongar and Gupta[8] used multi-criteria decision-making technique to study disassembly-to-order systems. For more information on product recovery and disassembly, see Gungor and Gupta[5], Lambert[10], Moyer and Gupta[12].

3. A DATA ENVELOPMENT ANALYSIS APPROACH FOR PRODUCT RECOVERY

Data envelopment analysis is a popular linear programming-based technique to evaluate the efficiency of a set of decision-making units. DEA was first developed by Charnes et al.[4] in 1978 and since then has mostly been used in health care, education, banking and manufacturing environments for benchmarking and for performance evaluation purposes.

3. 1. Introduction to DEA

There are different classifications of DEA algorithms based on various criteria. According to the “orientation” criterion DEA can be modeled as “input-orientated” or “output-orientated.” Input-orientated DEA focuses on proportionally reducing input quantities without changing the amount of output produced. On the other hand, output-orientated DEA models are interested in proportionally expanding the output quantities without altering the amount of input used. Further, “optimality scale” criterion also classifies four DEA models as “Increasing Returns to Scale (IRS),” “Decreasing Returns to Scale (DRS),” “Constant Returns to Scale (CRS)” and “Variable Returns to Scale (VRS).” Returns to scale refers to increasing or decreasing efficiency based on the size of the problem. For example, if selecting among ten candidates for a certain position opening can be 100 times easier than selecting from among sixty candidates, IRS would be assumed. The CRS model was first proposed by Charnes et al.[4] and assumes that all DMUs are operating on an optimal scale. In other words, CRS means that the inputs and outputs can be linearly scaled without decreasing or increasing the efficiency. This assumption of CRS may be valid over limited ranges, though its use must be justified. Combination of these two extreme cases results in the VRS model. The VRS model, which was first introduced by Banker et al.[1] as an extension of the CRS DEA model, assumes that not all DMUs operate on an optimal scale. In this paper, we use an output orientated CRS DEA model. Further explanation and justification of the model selection is given in the following sections.

A basic DEA model allows the introduction of multiple inputs and multiple outputs and obtains an "efficiency score" of each DMU with the conventional output/input ratio analysis. Using the notation given by Sarkis and Weinrach[17] the basic efficiency can be defined as:

$$E_{ks} = \frac{\sum_{y} O_{sy} v_{ky}}{\sum_{x} I_{sx} u_{kx}} \tag{1}$$

Where: E_{ks} is the efficiency or productivity measure of DMU s, using the weights of "test" DMU k; O_{sy} is the value of output y for DMU s; I_{sx} is the value for input x of DMU s; v_{ky} is the weight assigned to DMU k for output y; and u_{kx} is the weight assigned to DMU k for input x. The relative efficiency score of a test DMU k can be obtained by solving the following DEA ratio model (CCR) proposed by Charnes, Cooper and Rhodes[4]:

$$\begin{aligned} &\text{maximize} \quad E_{kk} = \frac{\sum_{y} O_{ky} v_{ky}}{\sum_{x} I_{kx} u_{kx}} \\ &\text{subject to:} \\ &E_{ks} \leq 1 \quad \forall \; s \\ &u_{kx}, v_{ky} \geq 0 \end{aligned} \tag{2}$$

The non-linear problem given in Eq. (2) can be converted to its equivalent linear program as follows (for further explanation on the model we refer the reader to Charnes et al.[3]):

$$\begin{aligned} &\text{maximize} \quad E_{kk} = \sum_{y} O_{ky} v_{ky} \\ &\text{subject to:} \\ &E_{ks} \leq 1 \quad \forall \; s \\ &\sum_{x} I_{kx} u_{kx} = 1 \\ &u_{kx}, v_{ky} \geq 0 \end{aligned} \tag{3}$$

Where the $\sum_{x} I_{kx} u_{kx} = 1$ constraint sets an upper bound of 1 for the efficiency ratio. As a result of Eq. (3), the technical efficiency value (E_{kk}^{*}) can obtain a maximum value of 1. Hence, if $E_{kk}^{*} = 1$, there is no other DMU more efficient than k for its selected weights. That is, DMU k is on the optimal frontier and is not dominated by any other DMU. If $E_{kk}^{*} < 1$ then DMU k does not lie on the optimal frontier and there is at least one DMU which is more efficient than DMU k. The CCR model given in Eq. (3) is run s times, once for each DMU to obtain the technical efficiency of each. The model is characterized by constant returns to scale (CRS) and, using duality, one can derive the dual of the model in the following form:

$$\begin{aligned} &\text{minimize} \quad \theta \\ &\text{subject to:} \\ &\sum_{s} \lambda_s I_{sx} - \theta I_{sx} \leq 0 && \forall \text{ Inputs } I \\ &\sum_{s} \lambda_s I_{sx} - \theta_{sy} - O_{ky} \geq 0 && \forall \text{ Outputs } O \\ &\lambda_s \geq 0 && \forall \text{ DMUs } s \end{aligned} \tag{4}$$

The above (Eq. 4) is the dual of the basic CCR model assuming constant returns to scale for all the inputs and outputs. It is also an input-orientated DEA model, which is the more common DEA formulation. The formulation of the dual of a basic output-orientated CRS model can be given as follows:

$$\begin{aligned} & \max \quad \Phi \\ & \text{subject to:} \\ & -\theta O_{sy} - \sum_s \lambda_s O_{sx} \geq 0 && \forall \text{ Outputs } O \\ & -I_{sx} - \sum_s \lambda_s I_{sx} \geq 0 && \forall \text{ Inputs } I \\ & \lambda_s \geq 0 && \forall \text{ DMUs } s \end{aligned} \tag{5}$$

Eq. (5) is the formulation for a basic output-orientated CCR model under the constant returns to scale assumption, which is also the formulation used in this paper. In order to convert the model to a variable returns to scale model, one may add the $\sum_s \lambda_s = 1$ constraint to the set of constraints.

Note that the variable Φ is the efficiency score for each DMU, which can also be represented as the technical efficiency (*TE*) by taking the reciprocal of this value (i.e., $TE = 1/\Phi$).

3. 2. Problem Formulation

Problem Statement

In this paper we consider an electronics product recovery facility that disassembles various types of EOL products for their demanded items and materials. The system under consideration initiates acquiring these EOL products from their last users or owners. Later, these products are brought into the facility where they are cleaned, sorted and prepared for further processing. Before any action is taken, these products are disassembled completely to their constituent parts. After these items are extracted from the product, there are four choices: (i) reselling the item to meet its corresponding demand, (ii) recycling the item and selling the material to meet its corresponding demand, (iii) storing the item with the expectation of a future demand, and (iv) proper disposal of the item with the least harm done to the environment. In the proposed model we aim to keep various outcomes of this operation under certain limits including financial (total profit), environmental (environmental benefit and environmental damage) and managerial (customer satisfaction).

The proposed model aims to find an "efficient" combination of EOL products keeping in mind the following. If the system gathers all the EOL products in such a way that all demands will be satisfied, the facility has very little control over the profit to be made and the environmental benefit and damage. On the other hand, if the decision maker can gain insight into the efficiency of each EOL product, then only the "better performers" could be considered for further processing, it would result in more profitable and/or more environmentally benign outcomes. With this aim the following algorithm is applied:

Proposed Model

Step 1. Consider all the EOL products that are on hand. Build and solve the linear programming (LP) model with the objective of maximizing the total profit.
Step 2. Calculate the required input and output measures for the DEA model for each EOL product from the results of the LP model.
Step 3. If the results are satisfactory, GO TO Step 7 else GO TO Step 4.
Step 4. Build and solve an output-orientated CRS DEA model for each EOL product. Obtain the efficiency scores of each EOL product.
Step 5. Observe the scores and identify any outsider (extremely inefficient) EOL products.
Step 6. Remove the inefficient EOL products without dramatically changing the demand levels, GO TO Step 1.
Step 7. STOP.

The development of the LP for the model and related revenue and cost functions followed by the model constraints are described below.

Revenue Functions:

There are two sources of revenues in the model, viz., the revenue from the sales of demanded materials (*RMS*) and the revenue from the sales of demanded components (*RPS*). The revenue functions can be written as follows:
RMS is obtained from the amount of materials sold ($\sum_j RQ_j$) and the market value of material obtained (RMV_j) from each item *j*. The amount of materials sold is a function of the number of item *j* recycled ($\sum_i R_{ij}$), the weight of component *j* ($\sum_i W_{ij}$) and the percentage of marketable material obtained from component *j* (PRC_j). Therefore, by summing the revenue over all components, RMS can be obtained as follows:

$$RMS = \sum_j (RQ_j . RMV_j) \tag{6}$$

where, RQ_j can be calculated as follows:

$$RQ_j = \sum_i R_{ij} . \sum_i W_{ij} . PRC_j \tag{7}$$

RPS is a function of the demand for component type *j* (D_j) and the unit sale price for component type *j* (PRM_j). Therefore, *RPS* can be mathematically expressed as follows:

$$RPS = \sum_j (D_j . PRM_j) \tag{8}$$

Cost Functions

The various costs considered in the model include: the take back cost (*TB*), transportation cost from collectors to the facility (*CTRCF*), transportation cost from facility to storage location (*CTRFS*), transportation cost from facility to disposal site (*CTRFD*), the cost of preparation of EOL products (*CAC*), the cost of destructive disassembly (*CDD*), the cost of nondestructive disassembly (*CND*), recycling cost (*CRE*), storage cost (*CST*) and disposal cost (*CDI*).
TB is a function of the number of EOL products ordered (Y_i) and the cost of each product (UTB_i). Therefore,

$$TB = \sum_i (Y_i . UTB_i) \tag{9}$$

CTRCF is a function of the number of EOL products ordered (Y_i) and the transportation cost per unit from collectors to the facility ($UCTRCF_i$). Therefore,

$$CTRCF = \sum_i (Y_i . UCTRCF_i) \tag{10}$$

CTRFS is a function of the number of components sent to storage (*NSTR*) and the transportation cost per unit from the facility to the storage location ($UCTRFS_j$). Therefore:

$$NSTR = \sum_j \sum_i V_{ij} \tag{11}$$

and

$$CTRFS = \sum_j \left(\sum_i V_{ij} \right) . UCTRFS_j \tag{12}$$

CTRFD is a function of the number of components sent to disposal (*NDIS*) and the transportation cost per unit from facility to the disposal site ($UCTRFD_j$). The number of components sent to disposal includes the non-demanded and non-stored components (L_{ij}). Therefore:

$$NDIS = \sum_j (\sum_i L_{ij}) \tag{13}$$

and

$$CTRFD = \sum_j (\sum_i L_{ij}).UCTRFD_j \tag{14}$$

CAC is a function of the number of EOL products ordered (Y_i) and the cost of preparing each product ($UCAC_i$). Therefore:

$$CAC = \sum_i Y_i.UCAC_i \tag{15}$$

CDD is the cost of destructive disassembly (considered for the components that are recycled for their material content or the components that are sent to landfills for proper disposal) and is a function of number of components to be recycled and disposed ($\sum_i (R_{ij} + L_{ij})$), the cost per hour (*cd*) and the time of disassembling each component (ddt_j). Therefore:

$$CDD = \sum_j \left(\sum_i (R_{ij} + L_{ij}) \right).cd.ddt_j \tag{16}$$

CND is the cost of non-destructive disassembly (considered for the components that are reused or the components that are sent to storage) and is a function of number of components to be reused and stored ($\sum_i (X_{ij} + V_{ij})$), the cost per hour (*cnd*) and the time of disassembling each component (dt_j). Therefore:

$$CND = \sum_j \left(\sum_i (X_{ij} + V_{ij}) \right).cnd.dt_j \tag{17}$$

CRE is a function of the amount of material recycled ($\sum_j (RQ_j)$) and the corresponding unit recycling cost ($UCRE_j$). Therefore:

$$CRE = \sum_j (RQ_j.UCRE_j) \tag{18}$$

CST is a function of the number of stored components ($\sum_i V_{ij}$), the volume of each component (υ_j) and the holding cost per unit volume (*h*). Therefore:

$$CST = \left(\sum_j (\sum_i V_{ij}).\upsilon_j \right).h \tag{19}$$

CDI is a function of the number of disposed components ($\sum_i L_{ij}$), and the corresponding unit disposal cost ($UCDI_j$). Therefore:

$$CDI = \sum_j (\sum_i L_{ij}) \; . \; UCDI_j \tag{20}$$

Total Profit Function

The total profit (*TPR*) is the difference between all the revenues and all the costs considered in the model. Therefore, *TPR* can be written as follows:

$$\begin{aligned} TPR = {} & RMS + RPS - TB - CTRCF - CTRFS - CTRFD \\ & - CAC - CDD - CND - CRE - CST - CDI \end{aligned} \tag{21}$$

Constraints

In this paper, we consider complete disassembly, implying that all the components in the product structure will be disassembled. Hence, the number of components retrieved from each EOL product ordered ($Y_i.Q_{ij}$) has to equal to the number of components that are reused (X_{ij}), recycled (R_{ij}), stored (V_{ij}) and disposed (L_{ij}). Therefore,

$$Y_i \,.\, Q_{ij} = (X_{ij} + R_{ij} + V_{ij} + L_{ij}),\ \forall\ i,j \tag{22}$$

Demand must be satisfied without allowing any backorders. Therefore, the demand constraints become:

$$D_j \le \sum_i X_{ij}, \forall\ j \tag{23}$$

The same reasoning also holds for the demand of material. The amount disassembled for recycling must exceed the demand by the amount lost $(DR_j \,.\, \gamma_j)$.

$$DR_j \le RQ_j\ , \forall\ j \tag{24}$$

The total number of components recycled (*NRC*) can be expressed as follows:

$$NRC = \sum_j DR_j \tag{25}$$

The total space (*TS*) occupied by the stored components have to be less than or equal to the total available space in storage (*AS*). *TS* is a function of the number of stored component *j* ($\sum_i V_{ij}$) and its corresponding volume (υ_j). Therefore:

$$TS = \sum_j (\upsilon_j \,.\, \sum_i V_{ij}) \text{ and} \tag{26}$$

$$TS \le AS \tag{27}$$

Note that the total number of reused components (*NRES*) is:

$$NRES = \sum_i \sum_j X_{ij} \tag{28}$$

All the variables must be non-negative integers. Thus,

$$\{Y_i\},\ \{X_{ij}\},\ \{R_{ij}\},\ \{V_{ij}\},\ \{L_{ij}\}\ \ge\ 0;\ \forall\ \ i, j. \tag{29}$$

Performance Measures

The model also includes three performance measures, viz., Total Environmental Benefit (*EB*), Total Environmental Damage (*ED*) and Total Customer Satisfaction (*CS*). These values are calculated using a ten-point scale regardless of the product type (scale unit: *su*). Here, while 1 is the lowest and 10 is the largest value; unit 5 represents the medium.

EB is the sum of all environmental benefit levels $(\sum_j ueb_j)$ for all resold and recycled items. Therefore:

$$EB = \sum_j (\sum_i X_{ij} + \sum_i R_{ij}).ueb_j \tag{30}$$

ED is the sum of all environmental damage levels $(\sum_j ued_j)$ for all disposed items. Therefore:

$$ED = \sum_j (\sum_i L_{ij}).ued_j \tag{31}$$

CS is the sum of all customer satisfaction levels $(\sum_j ucs_j)$ for all resold and recycled items. Therefore:

$$CS = \sum_j (\sum_i X_{ij} + \sum_i R_{ij}).ucs_j \quad (32)$$

4. CASE EXAMPLE

In this section, a numerical example is presented to foster a better understanding of the model. Consider ten EOL products as shown in Figure 1. Table 1 provides the data for the numerical example. Additional data includes: TB_i = {25, 32, 30, 35, 32, 35, 36, 35, 38, 40}, $UCTRCF_i$ = {10, 20, 10, 15, 10, 20, 10, 10, 15, 15}, *cnd* = \$14.69/hr., *cd* = \$12.5/hr., $UCTRFS_j$ = \$10/unit, $UCTRFD_j$ = \$12/unit, h = \$0.1/cu.in.

Using this data, the LP model was solved with the objective of maximizing the Total Profit Function (*TPR*). The relevant results are given in Table 2. After solving the LP problem of ten EOL products, the LP model is solved for each EOL product individually and separate results are then obtained. Using these results, a "single input-two output" CRS DEA model is established and solved for each EOL product. As a rule of thumb in DEA, input measures need to be selected from among the measures that improve when their values decrease while output measures should be chosen to be the ones that improve as their values increase. Therefore, in the proposed model the number of EOL products is selected as the input measure while the total profit (*TPR*) and total customer satisfaction (*CS*) functions are defined as the output measures of the model. DEA is modeled as "output-orientated" since proportionally expanding the output quantities (*TPR* and *CS*) without altering the amount of input used (here, the input measure is the number of EOL products that are taken-back from the last users and/or collectors) is the aim of the model. The results of these models are summarized in Table 3.

From Table 3, it is clear that EOL Products 8, 9 and 10 are inefficient compared to the rest of the EOL products. Therefore two more versions of LP models were solved, one with products 8 and 9 removed and the other with products 8, 9 and 10 removed. Note that demands for items that could only be met by disassembling the removed EOL products were also removed from the model. The results of these LPs are shown in the last two columns of Table 2. As observed from the table, when products 8 and 9 were removed, even though the total profit value per product had decreased, the remaining performance measures improved, i.e., the total environmental benefit per product and the total customer satisfaction per product values increased while the total environmental damage per product had decreased. When products 8, 9 and 10 were removed, the results did not improve. This is because a lot of demand could not be met when all three products were removed.

Depending on the results, the facility may decide to accept only EOL products 1-7 and 10 from the last users and collectors and may choose to meet only the related demand since it is more efficient as was noted above. The rest of the EOL products may be disassembled with another, more efficient group of EOL products in the future.

5. CONCLUSIONS

LP and DEA models were presented in order to determine the "efficient" types of EOL products to be considered for disassembly. The algorithm is practical, as it is easy to use and avoids inefficient disassembly decisions by providing environmentally benign solutions.

Table 1. Initial data for the LP model

#	Item	PRC_j (%)	W_j (lb/un.)*	D_j (un.)	DR_j (un.)	υ_j (cu.in/un.)	PM_j ($/un.lb)	RMV_j ($/un.lb)	$UCRE_j$ ($/un.lb)	ddt_j (hrs)	dt_j (hrs)	$UCDI_j$ ($/un.lb)	uebj (su/un.)	ued_j (su/un.)	ucs_j (su/un.)
1	Housing Assembly	0.85	0.5	3000	200	.8	10	.5	0.4	.004	.005	6	5	1	5
2	Housing Assembly	0.85	0.5	1200	200	.8	10	.5	0.4	.004	.005	6	5	1	5
3	Housing Assembly	0.85	0.5	1800	200	.8	10	.5	0.4	.004	.005	6	5	1	5
4	Housing Assembly	0.85	0.5	1200	100	.8	10	.5	0.4	.004	.005	6	5	1	5
5	Housing Assembly	0.85	0.5	1200	200	.8	10	.5	0.4	.004	.005	6	5	1	10
6	Housing Assembly	0.85	0.5	1800	200	.8	10	.5	0.4	.004	.005	6	5	1	10
7	Motherboard	0.95	0.2	1200	300	.6	15	.7	0.4	.004	.005	5	5	1	10
8	Motherboard	0.95	0.2	1200	200	.6	15	.7	0.4	.004	.005	5	5	1	10
9	Motherboard	0.95	0.2	1000	200	.6	15	.7	0.4	.004	.005	5	5	1	1
10	Motherboard	0.95	0.2	1500	0	.6	15	.7	0.4	.004	.005	5	5	1	1
11	Motherboard	0.95	0.2	1500	200	.6	15	.7	0.4	.004	.005	5	5	1	1
12	Motherboard	0.95	0.2	1800	200	.6	15	.7	0.4	.004	.005	5	5	1	1
13	64 MB RAM	0.90	0.1	1800	300	.5	10	.6	0.3	.006	.005	5	5	1	5
14	128 MB RAM	0.90	0.1	1200	200	.5	10	.6	0.3	.006	.005	6	1	5	5
15	256 MB RAM	0.90	0.1	1000	200	.5	10	.6	0.3	.006	.005	6	1	5	1
16	600 MHz CPU	0.85	0.2	1200	0	.8	15	.6	0.3	.006	.005	6	1	5	1
17	900 MHz CPU	0.85	0.2	1200	200	.8	15	.6	0.3	.006	.005	6	1	5	10
18	1000 MHz CPU	0.85	0.2	2000	200	.8	15	.6	0.3	.006	.005	6	1	5	5
19	Soundcard	0.95	0.1	1000	100	.8	20	.4	0.5	.002	.003	5	1	5	5
20	Soundcard	0.95	0.1	2000	300	.8	60	.4	0.5	.002	.003	5	1	5	5
21	Soundcard	0.95	0.1	1800	200	.8	80	.4	0.5	.002	.003	5	1	5	10
22	TV/Video Card	0.95	0.1	1800	100	.8	77	.4	0.5	.002	.003	5	1	5	10
23	TV/Video Card	0.95	0.1	1000	50	.8	85	.4	0.5	.002	.003	5	1	5	1
24	Graphics Card	0.95	0.1	1500	200	.8	164	.4	0.5	.002	.003	5	1	5	1
25	Graphics Card	0.95	0.1	1500	100	.8	250	.4	0.5	.002	.003	5	1	5	1
26	Graphics Card	0.95	0.1	1000	200	.8	280	.4	0.5	.002	.003	6	1	1	1
27	8 GB Hard Drive	0.55	0.2	1200	10	.7	20	.5	0.5	.002	.003	6	1	1	5
28	12 GB Hard Drive	0.55	0.2	1200	300	.7	20	.5	0.5	.002	.003	6	1	1	5
29	16 GB Hard Drive	0.55	0.2	1500	200	.7	20	.5	0.5	.002	.003	6	5	1	5
30	30 GB Hard Drive	0.55	0.2	1000	100	.7	20	.5	0.5	.002	.003	8	5	5	1
31	1.44 MB Floppy Drv	0.65	0.1	1000	200	.4	20	.5	0.5	.002	.003	8	5	5	1
32	40x CD-ROM	0.85	0.1	1200	0	.4	30	.6	0.3	.001	.002	6	5	10	1
33	52x CD-ROM	0.85	0.1	1000	200	.4	50	.6	0.3	.001	.002	7	5	10	5
34	24x10x40x CDR WR	0.85	0.1	1200	100	.4	60	.6	0.3	.001	.002	7	5	10	5
35	48x16x48x CD RWR	0.85	0.1	1500	200	.4	70	.6	0.3	.001	.002	7	1	10	5
36	8x24-DVD+CD WR	0.85	0.1	1000	30	.4	180	.5	0.5	.003	.002	6	1	5	5
37	10x24-DVD+CD WR	0.85	0.2	1500	200	.4	250	.5	0.5	.003	.002	6	1	5	5
38	16x40x DVD-ROM	0.85	0.2	1500	100	.4	100	.5	0.5	.003	.002	6	1	5	5
39	16x48x DVD-ROM	0.85	0.2	1200	200	.4	120	.5	0.5	.003	.002	6	1	5	1
40	Power Supply	0.45	0.6	1000	0	1.8	20	.6	0.3	.003	.002	15	1	10	5
41	Power Supply	0.45	0.6	1000	0	1.6	20	.6	0.3	.003	.002	15	1	10	1
42	Power Supply	0.45	0.6	1000	0	1.5	20	.6	0.3	.003	.002	15	1	10	5

* un. = unit

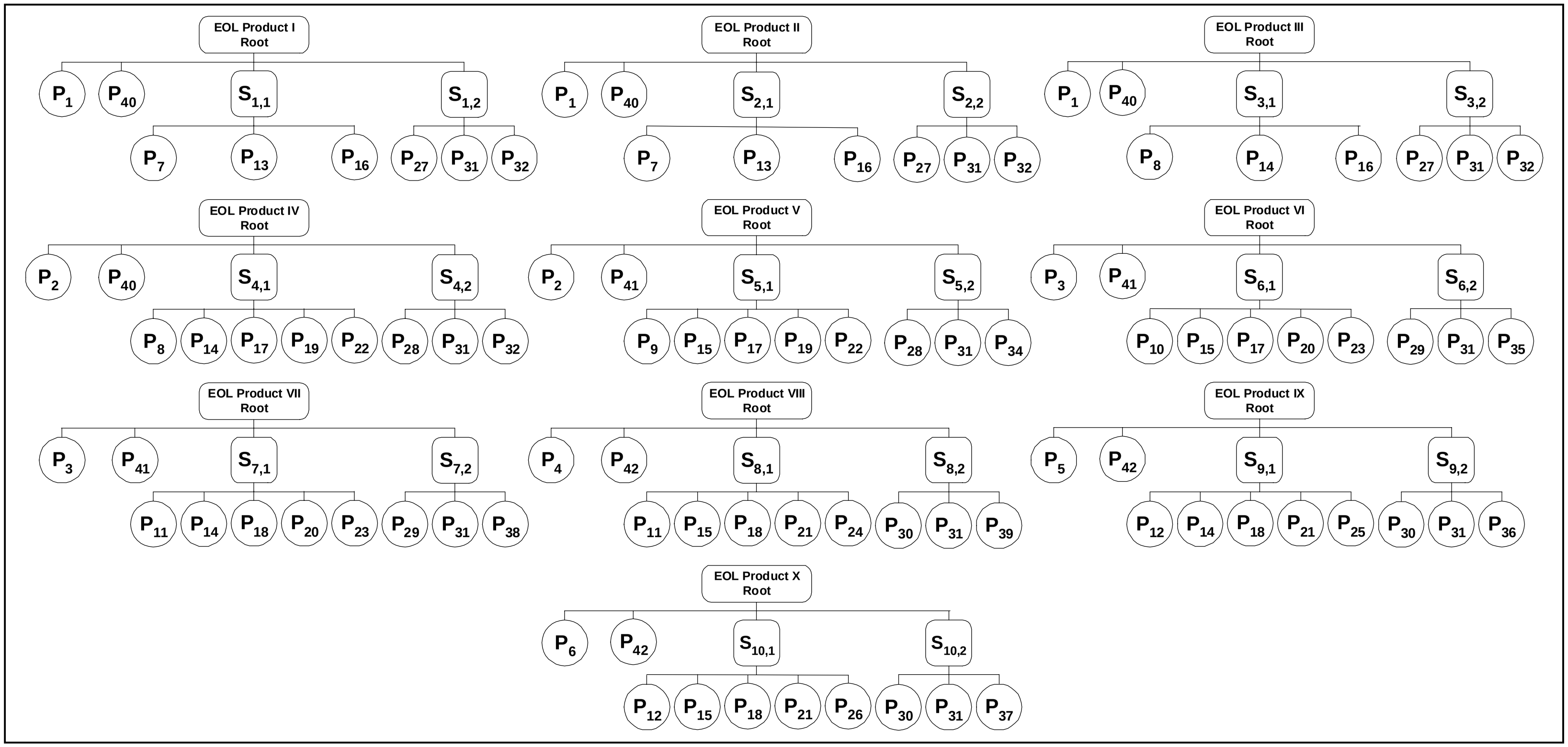

Figure 1. Original product networks and disassembly times

Table 2. Results of the LP models

Functions (per product)	All EOL products included	EOL products 8 and 9 are removed	EOL products 8, 9 & 10 are removed
Total Profit (*TPR*)	126.27	116.64	54.85
Environmental Benefit (*EB*)	1.37	1.58	1.51
Customer Satisfaction (*CS*)	20.70	23.93	21.65
Environmental Damage (*ED*)	3.40	2.70	3.69

Table 3. Output-orientated CRS DEA results

DMU	*Φ*	*TE*
1	1.00	1.00
2	1.57	0.64
3	1.00	1.00
4	4.35	0.23
5	8.42	0.12
6	2.39	0.42
7	5.77	0.17
8	104.00	0.01
9	104.00	0.01
10	90.00	0.01

6. APPENDIX

The notation used in this paper are summarized below:

υ_j	Volume of each item *j*
Φ	Efficiency of DMU
AS	Available storage space (cu. in.)
CAC	Cost of preparation of EOL products ($)
cd	Destructive disassembly cost per time unit ($/time unit)
CDD	Cost of destructive disassembly ($)
CDI	Cost of disposal ($)
CND	Cost of non-destructive disassembly ($)
cnd	Non-destructive disassembly cost per time unit ($/time unit)
CRE	Cost of recycling ($)
CST	Cost of storage ($)
CTRCF	Transportation cost from collectors to facility ($)
CTRFD	Transportation cost from facility to disposal ($)
CTRFS	Transportation cost from facility to storage ($)
ddt_j	Time required for disassembling item *j* (destructive) (time unit)
D_j	Resale demand for item *j* (unit)
DR_j	Recycling demand for material of item *j* (lb)
dt_j	Time required for disassembling item *j* (non-destructive) (time unit)
E_{ks}	Efficiency or productivity measure of DMU *s* using the weights of "test" DMU *k*
h	Holding cost per unit volume ($/cu.in.)
I_{sx_j}	Value for input *x* of DMU *s*

i	Index for EOL product
j	Index for item
k	Index for the test DMU
L_{ij}	Number of items j of product i to be disposed (unit)
$NDIS$	Number of disposed items (unit)
NRC	Total number of recycled items (unit)
$NRES$	Total number of reused items (unit)
$NSTR$	Total number of stored items (unit)
O_{sy}	Value of output y for DMU s
PRC_j	Recyclable percentage of item j (percentage/unit)
PRM_j	Resale value for reused item j (\$/unit)
Q_{ij}	Component multiplicity factor for item j of product i (unit)
R_{ij}	Number of items j of product i to be recycled (unit)
RMS	Materials sale revenue (\$)
RMV_j	Market value of material j (\$)
RPS	Item sale revenue (\$)
RQ_j	Amount obtained from recycling item j (lb)
RQ_j	Amount of material obtained from recycling item j (lb)
s	Index for DMU
TB	Take back cost (\$)
TE	Technical efficiency of DMU ($TE = 1/\Phi$)
TPR	Total profit value (\$)
TS	Total space occupied by the stored items (cu. in.)
$UCAC_i$	Unit cost of preparation for product i (\$/unit)
$UCDI_j$	Unit cost for disposing item j (\$/unit)
$UCRE_j$	Unit cost for recycling material k (\$/unit)
$UCTRCF_i$	Unit transportation cost from collectors to facility (\$/unit)
$UCTRFD_j$	Unit transportation cost from facility to disposal (\$/unit)
$UCTRFS_j$	Unit transportation cost from facility to storage (\$/unit)
u_{kx}	Weight assigned to DMU k for input x
UTB_i	Unit take-back cost for product i (\$/unit)
V_{ij}	Number of stored item j of product i (unit)
v_{ky}	Weight assigned to DMU k for output y
W_{ij}	Weight of item j in product i (lb)
X_{ij}	Number of reused item j of product i (unit)
Y_i	Number of EOL product i ordered (unit)

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